JURNAL
TEKNOLOGI AGRO-INDUSTRI
Vol. 11 No. 2; November 2024

e-ISSN 2598-5884
p-ISSN 2407-4624

Forecasting Using the Time Series Forecasting Model at SMEs Pempek Dang Tirta, Banyumas, Central Java

Firmansyah Firmansyah[1]*, Arina Fatharani[1], Ulfah Anis[1]

[1]Department of Agricultural Industry Technology, Universitas Bengkulu, Indonesia
*Email: ffirmansyah@unib.ac.id

Naskah diterima: 03 Agustus 2024; Naskah disetujui: 25 November 2024

ABSTRACT

Erratic product demand makes manufacturers create strategies to minimize unsold products. Products that are stored for a long time can cause losses, so forecasting is needed to calculate future product demand. The method used in this study uses a time series forecasting model at SMEs Pempek Dang Tirta. The quantitative data used covers the period January 2022-August 2023. The results of the calculation of the naïve bayes, exponential smoothing, Simple Moving Average (SMA), and Least Square models are presented in the table. The MAD (Mean Absolute Deviation) value indicates that the average deviation of the *yb* data from its mean value is about 1060.82 and The least square value obtained is 306.44 indicating that it could be the constant or intercept value of the resulting regression model.

Keywords: Forecasting; Moving Average; Time Series

INTRODUCTION

As a consequence of trade volatility, customer demands usually change, and overlooking this placement may result in under-estimating or overestimating inventory resulting in shortages or inefficiencies (Seyedan et al., 2023). So that management is needed in terms of forecasting. Demand forecasting is a critical topic for controlling a streamlined management plan (Nenni et al., 2013). Forecasting theory is a premise that last and present data or information could be used to have conjecture concerning the tomorrow (Petropoulos et al., 2022). Research on forecasting medium-term demand is much more finited, accounting for only 8% of all forecasting-related work (Liu et al., 2021). Demand forecasting entail conjecture future demand for a stuff or service utilizing last data and other outer or internal data (Tadayonrad & Ndiaye, 2023; Viverit et al., 2023). The demand for processed foods, including pempek, is highly unpredictable. According to Denis et al. (2006), companies may experience stockouts of up to 20% or overstocking of up to 15%, which directly impacts increased storage costs and lost sales.

The effects of poor forecasting are both stockouts and high inventories, outdated, weak service grades, husty orders, unstreamlined resource using and a bullwhip effect by way of the upstream supply chain. Until now, forecasting demand has become a challenge in the industrial world (Krishna et al., 2018; Nenni et al., 2013). Meanwhile, in the food industry, forecasting errors can cause big losses for producers because the food that has been produced can not be stored for a long time.

The initial measure in a demand forecasting problem is to specify the forecast breakdown by specifying the grade of aggregation to estimate. After determining the purposes and needs of the problem, the forecasting time series and time bucket need to be determined. Afterwards, the most suitable forecasting method has to be chosen based on past demand data, objectives, constraints, etc (Tadayonrad & Ndiaye, 2023). After collecting past demand data, it could be separated into a testing phase. One model that can be used in forecasting is the time series model (Hyndman & Athanasopoulos, 2018; Makridakis et al., 2020). The advantage of using a time series model is a better recognition and understanding of time patterns. Meanwhile, the weakness is the failure to build a non-linear model (Seyedan & Mafakheri, 2020). Time series models, especially including the autoregressive moving average (ARIMA) and its version, such as ARIMA and seasonal ARIMA most frequently utilized (Ma et al., 2016). This study aims to identify short-term patterns or trends in the demand data for orders at Pempek Dang Tirta, based on previous historical data.

LITERATURE REVIEW

Forecasting

Sales forecasting points to forecasting the sales amount of all or present stuff and services, a certain time in the future by a systematic sales forecast model built by last sales. Sales forecasting is critical in conventional wholesale and e-commerce, in addition to the exactness of the forecast affects the purpose, strategy, marketing, logistics, shed, and hoard management judgment of retailers, and another supply chain (Fildes et al., 2022). Appropriate sellings forecasting is essential for corporations operating in upper-holding capacity, weak-margin companies. Error in forecasting could lead to stock-outs or excrescent savings, causing an inability to fulfill demand and an enhancement in the fund company, and in both cases, unnecessary surcharge is incurred (Verstraete et al., 2019).

Forecasting is a main role in supply chain management as well. By producing more appropriate selling forecasts at the stock-storage unit tier, the bullwhip effect can be reduced and on-time delivery achieved, therefore fixing the exactness of supply chain management (Huang et al., 2019). In the case of supply chains, existing research concentrates on recognizing and criticizing the reasons that influence sellings forecasting (Sun et al., 2008), and building a recent sellings forecasting model (Sohrabpour et al., 2021). In addition, the practice of artificial intelligence for sellings forecasting and fixing sales forecast exactness (Huang et al., 2019). In general, demand forecasting is very challenging for many reasons, such as new product evolution, short product life cycles, and product returns (Petropoulos et al., 2022).

Naïve Bayes Model

The naïve bayes is a conventional statistical tool studying models extensively conducted in data mining such as sentiment classification of stuff reviews. Even though it is reasonably easy, its performance competitive impacts contrasted to a complicated model at the price of much weaker burden computing (Xia et al., 2011). Katkar et al. (2015) used a naïve bayes classifier using five years of sales data collected from multiple stores. The use of the naive bayes algorithm by Fan et al. (2017) was used to calculate sentiment indexes from the content of every online review and fuse them into the Bass/Norton model's imitation coefficients to fix forecast accuracy.

Smoothing Exponential

Exponential smoothing, progressive forecasting method, works based on the last forecasting plus the percentage forecast error (Karmaker, 2017). The exponential smoothing method is a powerful tool to detect time series, predict look-out demand, and lower storage charges which expand a smoothing and forecasting model that is intuitional, easy to imply, stable, and could pleasedly manage both additive and multiple seasonality, indeed as the time series contains multiple zero entries and a wide noise component (Ferbar Tratar et al., 2016). Arnomo et al. (2023) predicted the next period's sales period with the smallest error value using exponential smoothing with OutSystems platform. Svetunkov et al. (2023) applied the framework of multiple component time series of homogeneous families with exponential smoothing.

Least Square

The Least Square is a time series data method that needs previous selling data to forecast future demand. The Least Square method can be applied to create a straight trend line by using statistical methods (Widajanti & Suprayitno, 2020). Juliana et al. (2023) used the least square for forecasting cement sellings.

RESEARCH METHODS

This research uses a quantitative study by analyzing customer demand premier data from May 2022 - January 2024 at Pempek Dang Tirta. The data obtained is secondary data from the Pempek Dang Tirta monthly report. This study aims to identify short-term patterns or trends in the demand data for orders at Pempek Dang Tirta, based on previous historical data. Data processing using the help of MS. Excel 2010 with reference to calculations using moving average formulas (period n = 2 dan 3) and exponential smoothing (weight = 0.09).

Time Series Forecasting Methods

The time series model is broadly defined as a method based on analysis (Niknam et al., 2022).

Naive Bayes Method

A forecasting model which interprets the future demand is similar to the last demand. The naive method is described mathematically as follows: Naïve bayes method = Future period demand = last period demand

Naïve Method = X_{t-1} (1)

Simple Moving Average (SMA)

Moving average forecasting utilizes a number of past factual data to get forecasts.

$$\text{Moving Average} = \frac{\sum demand\ n\ periods\ earlier}{n} \quad (2)$$

Where n is the total of periods in the moving average. A pattern is detected, weights could be utilized to put more concern on the most present percentages. Moving averages with weights are also called Weighted Moving Averages. Weighted Moving Average can be described calculatingly as follows:

$$\text{Weighted Moving Average} = \frac{\sum(weight\ on\ period\ n)(demand\ for\ the\ period\ n)}{\sum Weight} \quad (3)$$

Exponential Smoothing

Exponential smoothing is an average forecasting method moved by weighting where the data points are weighted by the exponential function. Single Exponential Smoothing can be described mathematically as follows:

F_t = F_{t-1} + α (A_{t-1} - F_{t-1})

(4)

Where:

F_t = Recent forecast

F_{t-1} = Last forecast

α = Smoothing constant ($0 \leq \alpha \leq 1$)

A_{t-1} = last period's proper demand

The constant value can be determined by trial and error. But you can also use the formula below:

$\alpha = 2 / (n + 1)$

Where :

α = Constant value

n = Number of time periods

Least Square

Trend projection is a model of regulating tendency lines on a series of previous data, then designing the line in the look-out for medium-term or long-term forecasting. The equation is mathematically written as follows:

$y = a + bx$

(5)

Where :

y = The calculated measure of the variable to be predicted (the dependent variable)

a = y-axis crossover

b = Slope of the regression line (rate of change in y for the change in x)

x = Independent variable

RESEARCH DATA

Data collection is conducted from past sources, the number of pempek sales obtained from May 2022-January 2024 is listed in Table 1.

Table 1. The number of sales of SMEs Pempek Dang Tirta

No.	Month	Year	Sales Quantity (Packs/0.5 Kg)
1.	May	2022	122
2.	June	2022	154
3.	July	2022	156
4.	August	2022	200
5.	September	2022	255
6.	October	2022	120
7.	November	2022	353
8.	December	2022	344
9.	January	2023	244
10.	February	2023	345
11.	March	2023	443
12.	May	2023	345
13.	June	2023	341
14.	July	2023	321
15.	August	2023	356
16.	September	2023	335
17.	October	2023	358
18.	November	2023	345
19.	December	2023	390
20.	January	2024	423

Source: Processed data (Pempek Dang Tirta May 2022-January 2024)

Model Naïve Bayes

The naïve bayes model has low accuracy in recognising learned data, but has clear advantages when dealing with new types of attacks, and the training speed is faster (Zhang et al., 2022). Based on the table, the naïve bayes value in May 2022 is 122. It is taken based on the value in the previous month, namely the number of sales in January 2022.

Table 2. Naïve Bayes Method Testing Results

No.	Month	Year	Sales Quantity (Packs/0.5 Kg)	Naive Method
1.	May	2022	122	-
2.	June	2022	154	122
3.	July	2022	156	154
4.	August	2022	200	156
5.	September	2022	255	200
6.	October	2022	120	255
7.	November	2022	353	120
8.	December	2022	344	353
9.	January	2023	244	344
10.	February	2023	345	244
11.	March	2023	443	345
12.	May	2023	345	443
13.	June	2023	341	345
14.	July	2023	321	341
15.	August	2023	356	321
16.	September	2023	335	356
17.	October	2023	358	335
18.	November	2023	345	358
19.	December	2023	390	345
20.	January	2024	423	390

Source: Processed data by authors (2024)

Moving Average

The calculation of the moving average is carried out on a 2-month and 3-month period. The number of |*y1-ya*| obtained is 1050.25 and *y1-yb* is 1060.82. While the MAD (Mean Absolute Deviation) value of *ya* is 1050.25 and MAD (Mean Absolute Deviation) *yb* is 1060.82.

MAD *ya* $=\frac{1050.25}{18} = 1050.25$

MAD *yb* $= \frac{1060.82}{17} = 1060.82$

Table 3. Calculation Results of Moving Average Method

No.	**Month**	**Year**	**Sales Quantity (Packs/0.5 Kg) (*y1*)**	**MA (2 Months) (*ya*)**	**MA (3 Months) (*yb*)**	**(*y1*-*ya*)**	**y1-yb**	$\|y1 - ya\|$	***y1*-*yb***
1.	May	2022	122	**0**	**0**	**-**	**-**	-	-
2.	June	2022	154	0	0	-	-	-	-
3.	July	2022	156	138	0	18	-	18	-
4.	August	2022	200	155	144	45	56	45	56
5.	September	2022	255	178	170	77	85	77	85
6.	October	2022	120	227.5	203.66	-107.5	-83.66	107.5	83.66
7.	November	2022	353	187.5	191.66	165.5	161.34	165.5	161.34
8.	December	2022	344	236.5	242.6	107.5	101.4	107.5	101.4
9.	January	2023	244	174.25	408.5	69.75	-164.5	69.75	164.5
10.	February	2023	345	294	313.6	51	31.4	51	31.4
11.	March	2023	443	294.5	311	148.5	132	148.5	132
12.	May	2023	345	394	344	-49	1	49	1
13.	June	2023	341	394	377.6	-53	-36.6	53	36,6
14.	July	2023	321	343	376.3	-22	-55.3	22	55.3
15.	August	2023	356	331	335.6	25	20.4	25	20.4
16.	September	2023	335	338.5	339.3	-3,5	-4.3	3.5	4.3
17.	October	2023	358	345.5	337.3	12.5	20.7	12.5	20.7
18.	November	2023	345	346.5	349.66	-1.5	-4.66	1.5	4.66
19.	December	2023	390	351.5	346	38.5	44	38.5	44
20.	January	2024	423	367.5	364.33	55.5	58.56	55.5	58.56
								1050.25	1060.82

Source: Processed data by authors (2024)

Smoothing Exponential

The calculation of exponential smoothing is conducted by entering the current demand forecast with real demand data or actual demand data into the Exponential Smoothing formula. The calculation results obtained are F_{t-1} and F_t.

Table 4. Exponential Smoothing Calculation Results

No.	Month	Year	Sales Quantity (Packs/0.5 Kg)	F_{t-1}	F_t
1.	May	2022	122	200	192.98
2.	June	2022	154	200	195.86
3.	July	2022	156	100	105.04
4.	August	2022	200	150	154.5
5.	September	2022	255	200	204.95
6.	October	2022	120	150	147.3
7.	November	2022	353	300	304.77
8.	December	2022	344	400	394.96
9.	January	2023	244	300	294.96
10.	February	2023	345	300	304.05
11.	March	2023	443	300	312.87
12.	May	2023	345	300	304.05
13.	June	2023	341	300	303.69
14.	July	2023	321	300	301.89
15.	August	2023	356	300	305.04
16.	September	2023	335	300	303.15
17.	October	2023	358	300	305.22
18.	November	2023	345	310	313.15
19.	December	2023	390	300	192.98
20.	January	2024	423	300	195.86

Source: Processed data by authors (2024)

Least Square

The calculation of the least square value is done by counting, then a certain value is needed on the time variable (x) so that the sum of the time variable values is zero or $\Sigma x = 0$. So that the least square value obtained is 434. The x, xy, and x^2 values of the least square can be seen in table 5.

Table 5. Least Square Calculation Results

No.	Month	Year	Sales Quantity (Packs/0.5 Kg)	*X*	*Xy*	X^2
1.	May	2022	122	-19	-2318	361
2.	June	2022	154	-17	-2618	289
3.	July	2022	156	-15	-2340	225
4.	August	2022	200	-13	-2600	169
5.	September	2022	255	-11	-2805	121
6.	October	2022	120	-9	-1080	81
7.	November	2022	353	-7	-2471	49
8.	December	2022	344	-5	-1720	25
9.	January	2023	244	-3	-732	9
10.	February	2023	345	-1	-345	1
11.	March	2023	443	1	443	1
12.	May	2023	345	3	1035	9
13.	June	2023	341	5	1705	25
14.	July	2023	321	7	2247	49
15.	August	2023	356	9	3204	81
16.	September	2023	335	11	3685	121
17.	October	2023	358	13	4654	169
18.	November	2023	345	15	5175	225
19.	December	2023	390	17	6630	289
20.	January	2024	423	19	8037	361
			5950	0	17786	2660

Source: Processed data by author (2024)

$$a = \frac{\sum y}{n} = \frac{5950}{20} = 297.5$$

$$b = \frac{\sum xy}{\sum x^2} = \frac{17540}{2660} = 0.447058824$$

$$y = a + bx = 297.5 + 0.447058824\ (20)$$

$$= 306.4411765$$

CONCLUSION

Based on quantitative data obtained from the May 2022 to January 2024 period, the Mean Absolute Deviation (MAD) results show that the forecast using the 2-month moving average has a slightly lower MAD (1050.25) compared to the 3-month moving average (1060.82). This indicates that as the averaging period increases, the fluctuations in the forecast results decrease. The Least Squares method provides a more precise forecast, with a predicted value of 306.44 for January 2024, utilizing a linear approach to model the long-term sales trend.

ACKNOWLEDGMENT

Thank you to SMEs Pempek Dang Tirta who helped in providing research data.

REFERENCES

Arnomo, S. A., Yulia, & Ukas. (2023). Building The Prediction of Sales Evaluation on Exponential Smoothing using The OutSystems Platform. *ILKOM Jurnal Ilmiah, 15*(2), 222–228. http://dx.doi.org/10.33096/ilkom.v15i2.1529.222-228

Denis, D., St-Vincent, M., Imbeau, D., & Trudeau, R. (2006). Stock management influence on manual materials handling in two warehouse superstores. *International Journal of Industrial Ergonomics*, *36*(3), 191-201.

Fan, Z. P., Che, Y. J., & Chen, Z. Y. (2017). Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis. *Journal of Business Research*, *74*, 90–100. https://doi.org/10.1016/j.jbusres.2017.01.010

Ferbar Tratar, L., Mojškerc, B., & Toman, A. (2016). Demand forecasting with four-parameter exponential smoothing. *International Journal of Production Economics*, *181*, 162–173. https://doi.org/10.1016/j.ijpe.2016.08.004

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting*, *38*(4), 1283–1318. https://doi.org/10.1016/j.ijforecast.2019.06.004

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting*. OTexts: Melbourne, Australia.

Huang, T., Fildes, R., & Soopramanien, D. (2019). Forecasting retailer product sales in the presence of structural change. *European Journal of Operational Research*, *279*(2), 459–470. https://doi.org/10.1016/j.ejor.2019.06.011

Juliana, L. J. L., Lubis, A. P., & Lubis, I. A. (2023). Implementation Of The Least Square Method To Forecast Cement Sales. *Jurnal Ipteks Terapan*, *17*(1), 131-137. https://doi.org/10.22216/jit.v17i1.1625.

Karmaker, C. L. (2017). Determination of Optimum Smoothing Constant of Single Exponential Smoothing Method: A Case Study. *International Journal of Research in Industrial Engineering* , *6*(3), 184–192. https://doi.org/10.22105/riej.2017.49603

Katkar, V., Gangopadhyay, S. P., Rathod, S., & Shetty, A. (2015). Sales forecasting using data warehouse and Naïve Bayesian classifier. *2015 International Conference on Pervasive Computing: Advance Communication Technology and Application for Society, ICPC 2015*, *00*(c), 1–6. https://doi.org/10.1109/PERVASIVE.2015.7087133

Krishna, A., Akhilesh, V., Aich, A., & Hegde, C. (2018). Sales-forecasting of Retail Stores using Machine Learning Techniques. *Proceedings 2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions, CSITSS 2018*, 160–166. https://doi.org/10.1109/CSITSS.2018.8768765

Ma, E., Liu, Y., Li, J., & Chen, S. (2016). Anticipating Chinese tourists arrivals in

Australia: A time series analysis. *Tourism Management Perspectives*, *17*, 50–58. https://doi.org/10.1016/j.tmp.2015.12.004

Makridakis, S., Hyndman, R. J., & Petropoulos, F. (2020). Forecasting in social settings: The state of the art. *International Journal of Forecasting*, *36*(1), 15–28. https://doi.org/10.1016/j.ijforecast.2019.05.011

Nenni, M. E., Giustiniano, L., & Pirolo, L. (2013). Demand forecasting in the fashion industry: A review. *International Journal of Engineering Business Management*, *5*(SPL.ISSUE). https://doi.org/10.5772/56840

Niknam, A., Zare, H. K., Hosseininasab, H., Mostafaeipour, A., & Herrera, M. (2022). A Critical Review of Short-Term Water Demand Forecasting Tools—What Method Should I Use? *Sustainability (Switzerland)*, *14*(9), 1–25. https://doi.org/10.3390/su14095412

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., Boylan, J. E., Browell, J., Carnevale, C., Castle, J. L., Cirillo, P., Clements, M. P., Cordeiro, C., Cyrino Oliveira, F. L., De Baets, S., Dokumentov, A., … Ziel, F. (2022). Forecasting: theory and practice. *International Journal of Forecasting*, *38*(3), 705–871. https://doi.org/10.1016/j.ijforecast.2021.11.001

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-020-00329-2

Seyedan, M., Mafakheri, F., & Wang, C. (2023). Order-up-to-level inventory optimization model using time-series demand forecasting with ensemble deep learning. *Supply Chain Analytics*, *3*, 100024. https://doi.org/10.1016/j.sca.2023.100024

Sohrabpour, V., Oghazi, P., Toorajipour, R., & Nazarpour, A. (2021). Export sales forecasting using artificial intelligence. *Technological Forecasting and Social Change*, *163*(June 2020), 120480. https://doi.org/10.1016/j.techfore.2020.120480

Sun, Z. L., Choi, T. M., Au, K. F., & Yu, Y. (2008). Sales forecasting using extreme learning machine with applications in fashion retailing. *Decision Support Systems*, *46*(1), 411–419. https://doi.org/10.1016/j.dss.2008.07.009

Svetunkov, I., Chen, H., & Boylan, J. E. (2023). A new taxonomy for vector exponential smoothing and its application to seasonal time series. *European Journal of Operational Research*, *304*(3), 964–980. https://doi.org/10.1016/j.ejor.2022.04.040

Tadayonrad, Y., & Ndiaye, A. B. (2023). A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply Chain Analytics*, *3*(February), 100026. https://doi.org/10.1016/j.sca.2023.100026

Verstraete, G., Aghezzaf, E. H., & Desmet, B. (2019). A data-driven framework for predicting weather impact on high-volume low-margin retail products. *Journal of*

Retailing and Consumer Services, *48*(August 2018), 169–177. https://doi.org/10.1016/j.jretconser.2019.02.019

Viverit, L., Heo, C. Y., Pereira, L. N., & Tiana, G. (2023). Application of machine learning to cluster hotel booking curves for hotel demand forecasting. *International Journal of Hospitality Management*, *111*(March), 103455. https://doi.org/10.1016/j.ijhm.2023.103455

Widajanti, E., & Suprayitno, S. (2020). Implementasi Metode Least Square Untuk Memprediksi Penjualan Susu Perah (Studi Pada Kud Cepogo Kabupaten Boyolali). *Research Fair Unisri*, *4*(1). https://doi.org/10.33061/rsfu.v4i1.3429

Xia, R., Zong, C., & Li, S. (2011). Ensemble of feature sets and classification algorithms for sentiment classification. *Information Sciences*, *181*(6), 1138–1152. https://doi.org/10.1016/j.ins.2010.11.023

Zhang, C., Jia, D., Wang, L., Wang, W., Liu, F., & Yang, A. (2022). Comparative research on network intrusion detection methods based on machine learning. *Computers and Security*, *121*, 102861. https://doi.org/10.1016/j.cose.2022.102861